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ORIGINAL PAPER

Modeling susceptibility to deforestation of remaining ecosystems in North Central Mexico with logistic regression

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Abstract: Determining underlying factors that foster deforestation and delineating forest areas by levels of susceptibility are of the main challenges when defining policies for forest management and planning at regional scale. The susceptibility to deforestation of remaining forest ecosystems (shrubland, temperate forest and rainforest) was conducted in the state of San Luis Potosi, located in north central Mexico. Spatial analysis techniques were used to detect the deforested areas in the study area during 1993−2007. Logistic regression was used to relate explanatory variables (such as social, investment, forest production, biophysical and proximity factors) with susceptibility to deforestation to construct predictive models with two focuses: general and by biogeographical zone. In all models, deforestation has positive correlation with distance to rainfed agriculture, and negative correlation with slope, distance to roads and distance to towns. Other variables were significant in some cases, but in others they had dual relationships, which varied in each biogeographical zone. The results show that the remaining rainforest of Huasteca region is highly susceptible to deforestation. Both approaches show that more than 70% of the current rainforest area has high and very high levels of susceptibility to deforestation. The values represent a serious concern with global warming whether tree carbon is released to atmosphere. However, after some considerations, encouraging forest environmental services appears to be the best alternative to achieve sustainable forest management.

Keywords: GIS; land use change; proximity factors; statistical modeling; ROC curve; regional forest planning

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Introduction

Mexico is the third of five countries (Brazil, Gabon, Mexico, Papua New Guinea and Indonesia) that was recorded the greatest decrease areas of primary forest in the last 20 years. However, Mexico is also among the countries with more than 10 million ha of forest designating more than 70% of forest area for multiple uses. It is sixth place among the ten countries with the largest annual increase in area of planted forests (1990−2010), and seventh place among the countries with largest area of reforestation in 2005 (FAO 2010). This information reveals the government's willingness to minimize the effects of forest degradation, because when an ecosystem is destroyed, restoration is very complicated. The least difficult would be the recovery of water services, while the soil is not completely lost, before it becomes impossible to recover the biodiversity of the genetic bank of the original species (Martínez et al. 2009; Fuller et al. 2010).

Land use changes have been studied in various locations around the world, under different circumstances and purposes with different approaches and methodologies. Such investigations results were used to solve basic questions about what happened and how, by using change matrices obtained via cross-tabulating maps by photointerpretation (Chapa-Bezanilla et al. 2008) or by classifying satellite imagery with statistical algorithms (Boletta et al. 2006; Long et al. 2008; Chai et al. 2009; Calvo-Alvarado et al. 2009). The application of statistical models is useful in determining the statistically significant variables and their relative importance to answer this question (Pineda-Jaimes et al. 2010). These studies are essential when designing programs on ecosystem restoration and determining priority areas for conserving forest resources (Averna-Valente and Vetorazzi 2008).

There are several statistical approaches for examining the causes of deforestation. Multiple linear regression with social

and economic variables was used to explain the rates of deforestation (Culas 2007; Arcand et al. 2008; Freitas et al. 2010), and logistic regression was used to model deforestation and the susceptibility of a site was determined to be cleared (Chowdhury 2006; Echeverria et al. 2008). Also, autoregressive models were used to take spatial autocorrelation into account in the analysis (Dendoncker et al. 2007), while geographically weighted regression was used as evidence that the factors influencing deforestation processes are spatially variable (Pineda-Jaimes et al. 2010).

San Luis Potosi is a biodiverse Mexican state with arid, temperate and tropical ecosystems. There are different degrees of susceptibility to deforestation in this state. The tropical vegetation of the biogeographical zone called the Huasteca ("Huasteca zone" from now on) was significantly affected by deforestation projects promoted in the recent past for the establishment of intensive agriculture, and are now extensive areas under cultivation (Reyes-Hernández et al. 2006). The timely assessment of susceptibility to deforestation of remaining vegetation lies in the ability to make decisions that could change the fate of forest resources. Thus, the objectives of this study were: (1) to analyze the effect of independent variables such as social and biophysical factors, investment and proximity (in general and by biogeographical zone) on deforestation processes that were detected in official vegetation and land use maps (1993–2007) of the state of San Luis Potosi using logistic regression; (2) to determine the susceptibility to deforestation of the remaining shrubland, temperate forest and rainforest vegetation as a tool in regional forest planning; (3) to evaluate the performance of each model with the ROC (Receiver Operating Characteristic) curve and 10-fold cross validation.

Materials and methods

San Luis Potosi is a Mexican state (extending from 24°29'27" N to 21°09'33" N and from 98°19'48" W to 102°18'10" W) having an area of 6 116 360.9 ha distributed in 58 municipalities. Located at the upper limit of the intertropical zone, four biogeographical zones were divided into: Altiplano, Media, Centro and Huasteca. Both the mountains of Sierra Madre Oriental (north to south) and moist winds from the Gulf of Mexico are factors for shaping the climatic and ecological conditions of the biogeographical zones. Slopes facing the sea receive moist winds, and the precipitation is above 1 400 mm (Media and Huasteca area), so the vegetation remains green in the most of one year. Climatic conditions of Huasteca zone allows the cultivation of a variety of tropical plants, which can yield three crops in one year in some places (Rzedowski 1963). This creates special interest in converting forests into agricultural and grazing land. As the winds penetrate the continent (the Centro and Altiplano zone), the precipitation decreases to less than 600 mm, favoring the growth of arid vegetation (Fig. 1a and 1b).

Vegetation and land use maps series II (1993) and IV (2007) made by the National Institute of Statistics and Geography of Mexico (INEGI) (the scale of 1:250 000) in vector format were used. The older vector map was co-registered to the current vector map assuming that the latter was correctly georeferenced. The map legend was standardized by using a level-two (vegetation type) classification scheme (Velázquez et al. 2002), to increase the reliability issue of the cartographic information. The maps were validated with 330 sampling sites obtained from the National Forest Inventory of Mexico (2004–2006) using confusion matrices, and Series II (1993) had an overall reliability of 89.7% and 86.4% Kappa, while Series IV (2007) had 85.7% and 81.3%, respectively. A deforestation map was made by intersecting these two maps and identifying polygons that changed from shrubland, forest and rainforest to treeless land use. Spatial work was done with ArcMap 9.1 and Idrisi Andes software.

As explanatory variables, five groups of variables were included (Table 1): (1) population, (2) investment, (3) forest production, (4) biophysical factors, and (5) proximity. The variables in groups 1, 2 and 3 were obtained from the INEGI State and Municipal System Database (SIMBAD). Biophysical variables were obtained from the digital elevation model (DEM) of the Shuttle Radar Topography Mission (SRTM) with a pixel size of 90 m, while proximity variables were generated from the INEGI 1:250 000 scale maps. The explanatory variables were normalized by logarithmic transformation of the form ln (X_k+1), where, "ln" is the Natural logarithm, X_k is explaining variable to avoid the influence of the units of measure in the selection of variables (Pineda-Jaimes et al. 2010; Deng et al. 2010). Variables were converted to raster as a reference for the municipal boundaries of the study area obtained from the National Geostatistical Framework version 4.1 in National Institute of Statistics and Geography (INEGI). The relationship between the variables of the group corresponding to population growth and the dependent variable (forest loss) is based on the assumption that it is the population itself acting on the municipal territory. It does not take into account social actors that likely act within the municipality but are not part of it. Likewise, one should consider that the socioeconomic variables used are averages and assume that the entire municipality is homogeneous (Pineda-Jaimes et al. 2008). All information was handled in UTM projection, Zone 14, Datum ITRF92 and 90 m spatial resolution.

Logistic regression was applied to (1) examine the relationship between deforestation and social, economic, biophysical and proximity factors; (2) determine susceptibility to deforestation in each of the biogeographical zones of the study area. This type of regression is used for binary response variables and does not require assumptions such as normality in the data (Mallinis and Koustias 2009). $\ln\left(\frac{p}{q}\right)$ is used in this model, where p is the probability of occurrence and q is the probability of non-occurrence. The logit function is used to transform the linear combination of explanatory variables on a scale of measurement for binomial data (forested = 0 and deforested = 1). The probability of deforestation is expressed by the model as follows:

$$p(Y=1\mid \mathrm{X})=\frac{e^{(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)}}{1+e^{(\beta_0+\beta_1X_1+\ldots+\beta_kX_k)}} \tag{1}$$

Where, X_k is the explaining variable, and β_k is the parameter to be estimated. Most of the literatures refer to the terms probability and susceptibility as synonymous. We preferred the term susceptibility, because estimated values do not assure that deforestation will occur, and they just are the measures of a terrain's susceptibility to deforestation based on significant explaining variables.

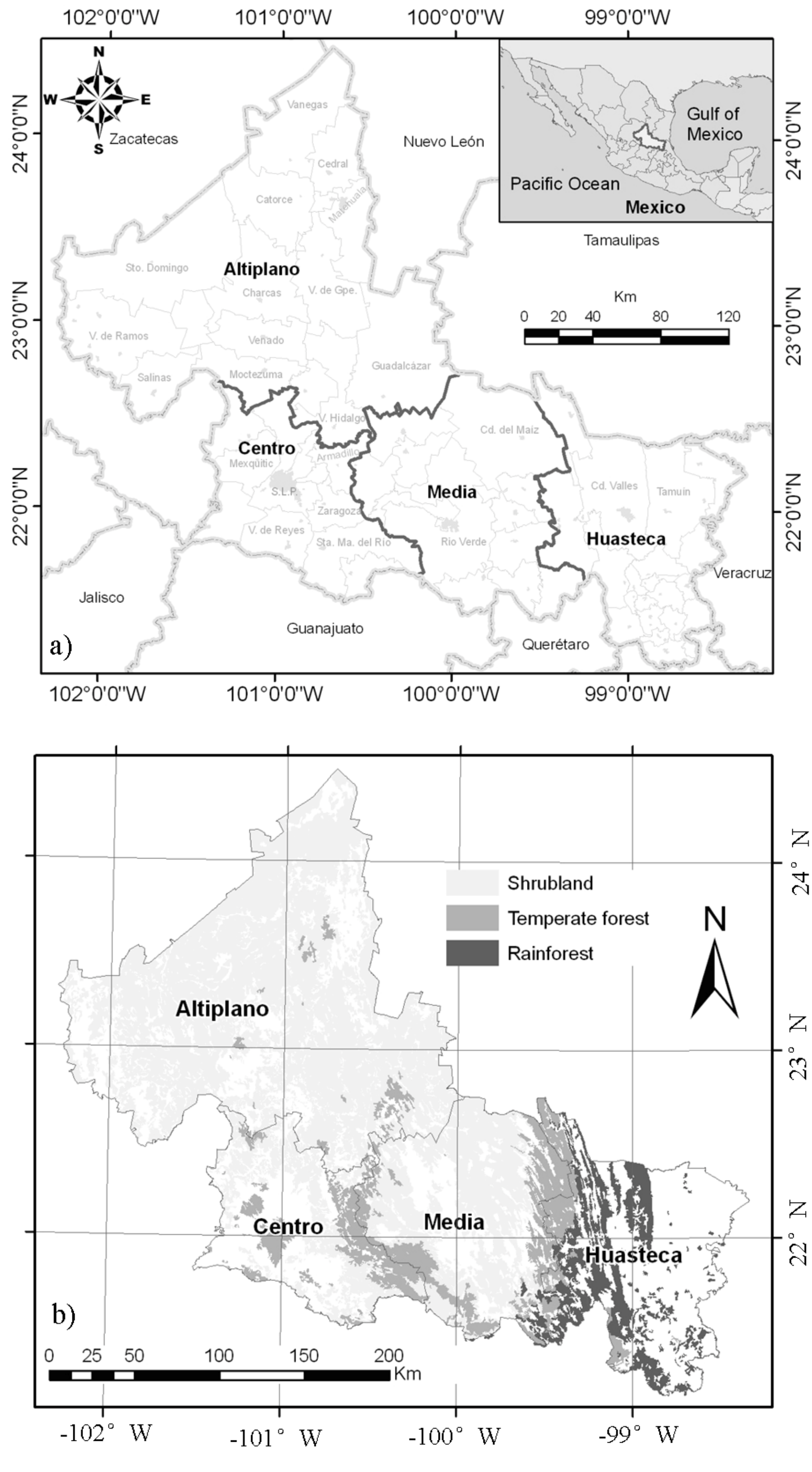

Fig. 1 Location of the study area: a) political boundaries; b) remaining ecosystems.

Table 1. Independent variables

Group	No.	Variable	Description	Source
1	1	POPD	Population density (hab·km^{-2})1995	INEGI
	2	DPOPD	Difference in population density (%) (1995–2005)	INEGI
	3	HDI	Human development index (%) (2000)	INEGI
	4	PFWOOD	Population using firewood for cooking (%) (2000)	INEGI
	5	SCHOOL	Level of education (average number of years spent in school) (2005)	INEGI
2	6	CRED	Number of housing loans (1994–2007)	INEGI
	7	PCAMPO	Number of loans to farmers granted by a Mexican federal government program called PROCAMPO to finance crops such as maize (1994–2007)	INEGI
3	8	WOOD	Wood production (m^3) (1994–2007)	INEGI
	9	NWOOD	Non-wood production (ton) (1994–2007)	INEGI
4	10	ELEV	Elevation above sea level (m)	SRTM
	11	SLOPE	Slope (%)	SRTM
5	12	DAGR	Distance to rainfed agriculture (m) (1993)	INEGI
	13	DGRASS	Distance to grasslands (m)	INEGI
	14	DRIVER	Distance to rivers (m)	INEGI
	15	DROAD	Distance to roads (m)	INEGI
	16	DTOWN	Distance to towns <2500 inhabitants (m)	INEGI

Sometimes the presence of autocorrelation in deforestation is desirable, especially when selecting priority areas for restoring or protecting forests (Pompa-García 2011). But when application statistical models and regression parameters have to be estimated, one assumption must be made: observations should be independent (Legendre 1993; Barrett et al. 2010). Because deforestation data used in this study were obtained from a binary rasterization of polygons generated by intersecting vector maps of vegetation and land use, samples spaced in the interval of 500 m were taken to minimize the effect of spatial autocorrelation in model parameter estimation (Echeverria et al. 2008). After sampling, spatial distribution of evaluation sites was assessed with the Moran index that takes values between -1 and +1, where, 1 denotes clustering, -1 denotes dispersion, and 0 is an evidence that the spatial pattern is completely random. Significance was evaluated using the Z statistic, where a non-significant value ($-1.96 \leq Z \leq 1.96$) was wanted to find, in order to deduce that the sampling was effective for minimizing spatial autocorrelation in the distribution of deforestation evidence (Fuller et al. 2010).

The model parameters were estimated using PROC LOGISTIC in SAS software (SAS Institute Inc. 2004). Final explanatory variables of the model were chosen considering two criteria: (1) minimizing the multicollinearity between the explanatory variables (Sifuentes-Amaya and Ramírez-Valverde 2010) by eliminating those variables with a variance inflation factor (VIF) higher than 5, although some authors recommend a maximum of 10 (Alix-Garcia et al. 2010); (2) the significance of the variables (p <0.05). The estimations of susceptibility to deforestation were multiplied by a Boolean mask of forest areas obtained with the current vegetation map.

The model's goodness of fit was carried out using the receiver operating characteristic (ROC) plot. The ROC plot ("ROC curve" from now on) compares binary data over the entire range of predicted sensitivities and indicates the model's ability to determine the susceptibility to deforestation in various spatial locations (Braimoh and Onishi 2007). A ROC curve plots the percentage of true positive values (sensitivity) against the actual percentage of negative (specificity), and it gathers the same information from a confusion matrix but in a more descriptive and robust way (Hamel 2008). The area under the ROC curve (AUC) is an indicator that quantifies the goodness of fit of the models and typically ranges from 0.5 to 1. A value above 0.5 is statistically better than random, a value above 0.7 is normally considered acceptable, above 0.8 is excellent and more than 0.9 is exceptional (Beguería 2006; Hu and Lo 2007). To validate the estimates of AUC, a SAS script was done (10-fold cross validation) as described by Gönen (2007).

Results and discussion

It is widely recognized that spatial autocorrelation in the dependent variables may violate the assumption that observations should be independent, directly impacting significance and performance of the statistical model (Barrett et al. 2010). Moran's index obtained for the dependent variable was close to zero and a non-significant Z-value (-1.96 to 1.96) in all models. This confirms that spatial autocorrelation was effectively minimized after sampling (Echeverria et al. 2008; Bhattarai et al. 2009; Fuller et al. 2010).

Only those variables that were statistically significant (p <0.05), and with no multicollinearity (VIF < 5) between them, were kept in each model. The relative importance for each variable is shown in Fig. 2. The standardized coefficients are plotted in Fig. 2. The positive or negative signs indicating the direction of the relationship can be seen in Table 2. For the correct interpretation of the variables selected, the partial effects of four most significant variables for the General model are shown in Fig. 3. Forest vegetation at an elevation lower than 50 m above sea level, or in municipalities with a population density of more than 110.9

inhabitants·km^{-2}, or 106.9 km away from agriculture lands, have greater susceptibility to deforestation. Although the distance to grassland is statistically significant, its partial effect is very small, showing susceptibility values slightly above 0.2 (Fig. 3c). For the remaining variables it is same with high significance but with small values of importance.

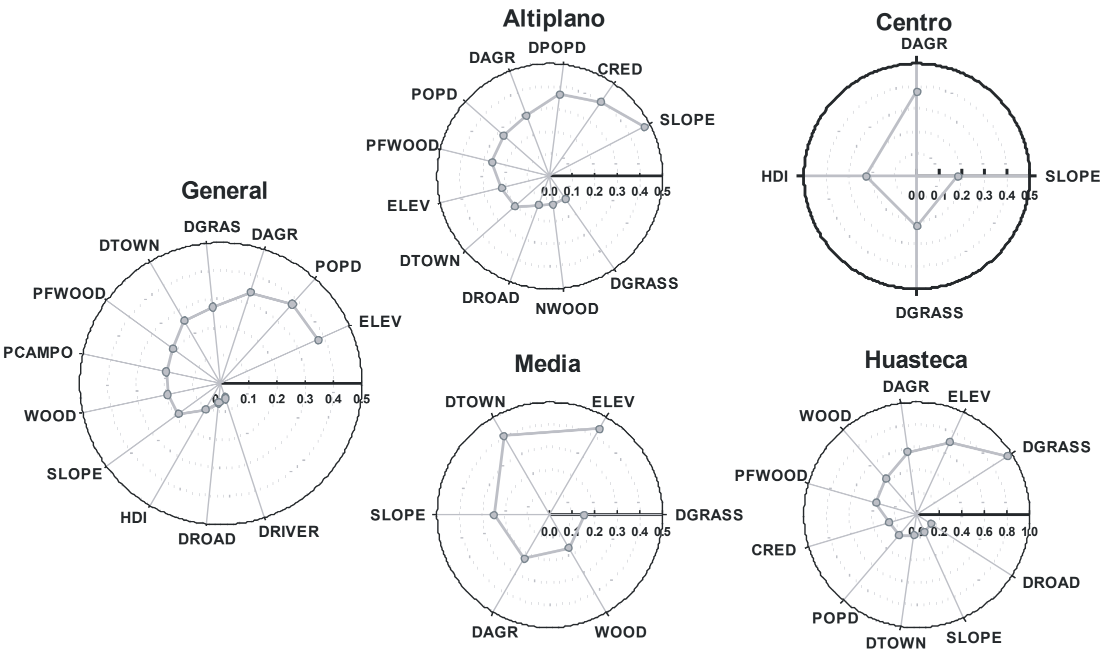

Fig. 2 Standardized coefficients that indicate the importance of each variable in the model obtained. POPD, Population density (hab·km^{-2}) (1995); DPOPD, Difference in population density (%) (1995-2005); HDI, Human development index (%) (2000); PFWOOD, Population using firewood for cooking (%) (2000); SCHOOL, Level of education (average number of years spent in school) (2005); CRED, Number of housing loans (1994-2007); PCAMPO, Number of loans to farmers granted by a federal government program called PROCAMPO to finance agriculture (1994-2007); WOOD, Wood production (m^3) (1994-2007); NWOOD, Non-wood production (ton) (1994-2007); ELEV, Elevation above sea level (m); SLOPE, Slope (%), DAGR, Distance to rainfed agriculture (m) (1993); DGRASS, Distance to grasslands (m); DRIVER, Distance to rivers (m); DROAD, Distance to roads (m) and DTOWN, Distance to towns < 2500 inhabitants (m).

Table 2. Parameters estimated for logistic regression models.

No	Variable	Model				
		General	Altiplano	Centro	Media	Huasteca
	Intercept	14.7746	-10.6060 ns	21.0795	25.0443	-2.5018 (*p* = 0.0175)
1	POPD	0.7448	0.7605 (*p* = 0.0015)	ns	ns	-0.7278
2	DPOPD	ns	7.1829 (*p* = 0.0015)	ns	ns	ns
3	HDI	-2.4547 (*p* = 0.0002)	ns	-5.4982	ns	ns
4	PFWOOD	0.6541	1.0342 (*p* = 0.0010)	ns	ns	1.3505
5	SCHOOL	v = 12.48	v = 55.37	ns	ns	v = 10.45
6	CRED	ns	-0.9422	ns	ns	0.3673
7	PCAMPO	-0.5172	ns	ns	ns	ns
8	WOOD	0.0900	ns	ns	-0.0822	0.2014
9	NWOOD	ns	0.0710 (*p* = 0.0302)	ns	ns	ns
10	ELEV	-0.5086	-2.3981 (*p* = 0.0012)	ns	-2.4724	-1.1309
11	SLOPE	-0.3750	-1.1142	-0.3577 (*p* = 0.002)	-0.4923	-0.3531 (*p* = 0.0003)
12	DAGR	0.2715	0.2005	0.2821	0.1975	0.4991
13	DGRASS	0.2012	-0.1070 (*p* = 0.002)	0.1397	-0.1640	0.7473
14	DRIVER	0.0719 (*p* = 0.0036)	ns	ns	ns	ns
15	DROAD	-0.0906	-0.1885 (*p* = 0.0002)	ns	ns	-0.1856 (*p* = 0.0003)
16	DTOWN	-0.5070	-0.4543	ns	-0.8410	-0.4117

For all variables that were significant at $p < 0.0001$, p values were omitted; for the others, p values are presented between parentheses; v = vif > 10; ns = non-significant.

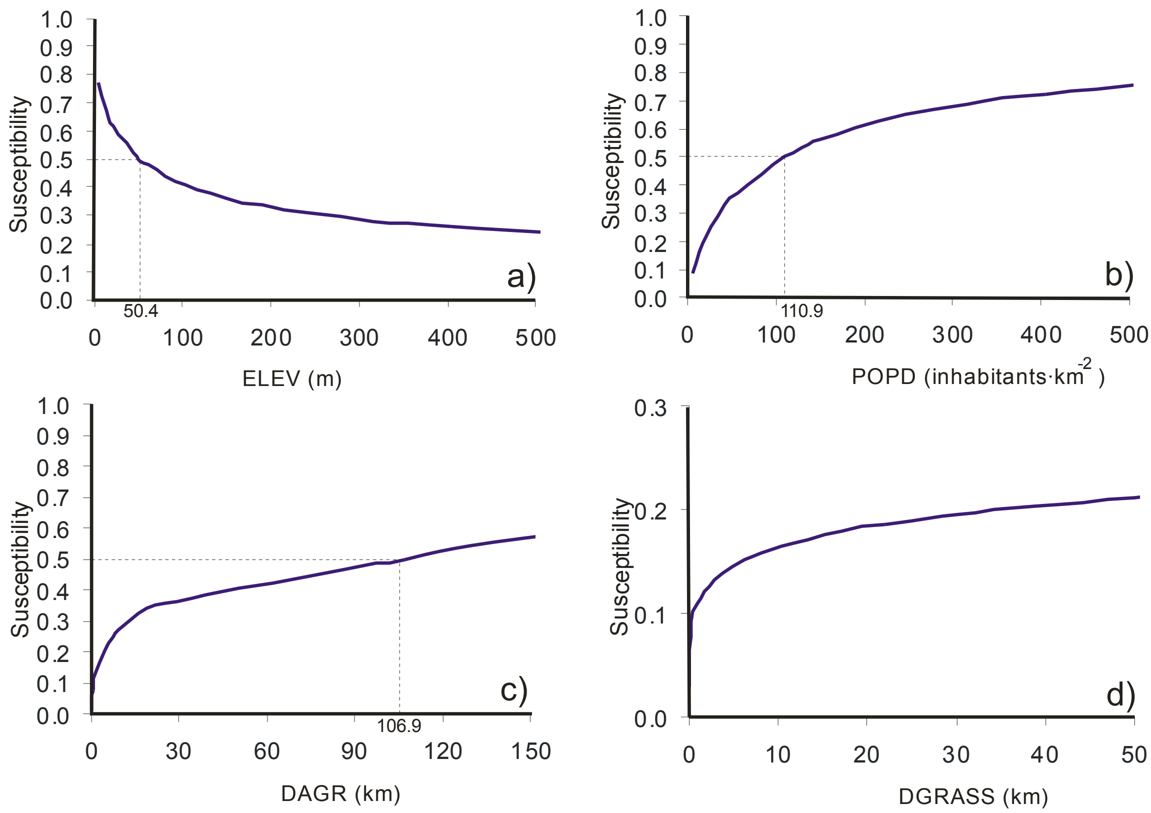

Fig. 3 Partial effects of the four most important significant variables in susceptibility to deforestation of model general: a) elevation, b) population density, c) distance to rainfed agriculture, d) distance to grassland.

For the Altiplano model, where shrubland is the dominant vegetation (arid climate), deforestation was observed on less steep slopes, in municipalities with fewer housing loans and higher population growth, as well as in the places farthest from agricultural lands and closest to small towns, with highest non-timber production and increased use of firewood for cooking. Interestingly, in this biogeographical zone, both the HDI and PCAMPO were not significant.

In the Centro zone, where the capital city of the state of San Luis Potosi is located, the logistic model showed interesting variations. Deforestation was most likely in remote areas far from rainfed agriculture and grasslands in municipalities with a lower HDI and less steep relief. In the Media biogeographical zone, deforestation was more likely at lower altitudes, influenced by the proximity of the Huasteca in the flat areas closest to towns because of better accessibility. And, in remote areas of rainfed agriculture deforestation was interpreted as wooded municipalities with lower timber production possibly due to lack of forest management programs, which encourages illegal logging that is not counted in the statistics and in places closer to the grasslands. Finally, in the Huasteca zone, the areas more prone to deforestation were those farthest from the grasslands and rainfed agriculture at lower elevations, in municipalities with more timber production and increased consumption of firewood for cooking, and in those with higher incidence of credit for housing but lower population density, and in places closer to small towns, closer to roads and with flat topography.

Since all models were statistically significant, ROC curves also behaved consistently (Fig. 4). For both the General and Huasteca models, the ROC curve showed balanced performance between true positive and true negative classifications by the symmetry of the ROC curve. The other models had a slight tendency to liberal performance, that is, they were more likely to estimate positive values. The logistic model for the Centro zone resulted in a smaller AUC (0.67) and coincided with the smallest number of statistically significant explanatory variables (4 variables). The other models had acceptable performance: General (AUC = 0.83), Altiplano (AUC = 0.84), Media (AUC = 0.78), and Huasteca (AUC = 0.86). And they matched those reported by different authors (Beguería 2006; Hu and Lo, 2007, Rutherford et al. 2008; Dendoncker et al. 2007). The AUC obtained with the 10-fold cross validation is shown in Fig. 4c. The highest values were obtained for the Huasteca model (0.82 to 0.89), while the smallest were for the Centro model (0.58 to 0.70). The Huasteca region, rich in forest resources and a marked variation in the explanatory variables, allowed a better goodness of fit for the model. While in the Centro region, where deforestation is rare and has less variation, the explanatory variables yielded poor adjustment, although statistically significant,

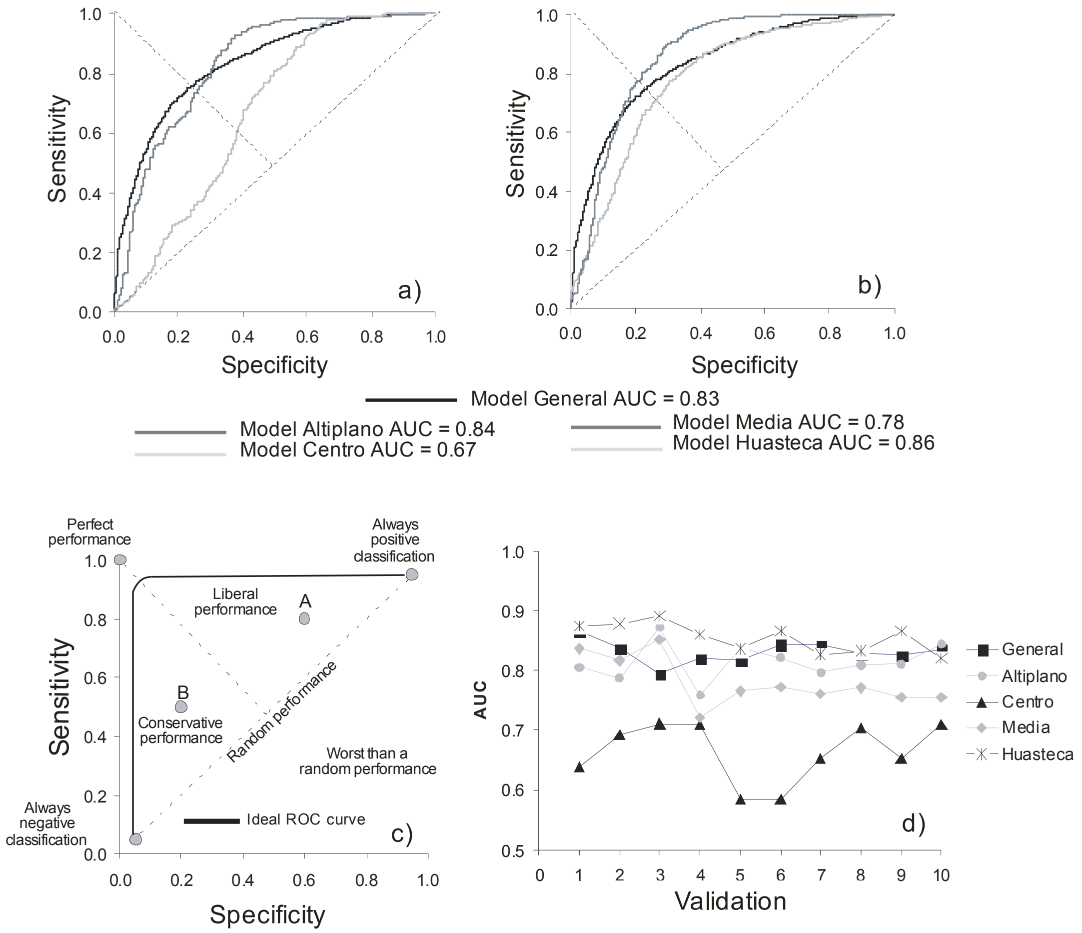

Fig. 4 ROC curve. a) and b) models constructed, c) ideal model adapted from Hamel (2008) and d) results from 10-fold cross validation.

In Fig. 5, more balanced estimations can be observed in the General model, compared with the models constructed by biogeographical zone (Fig. 6). In both approaches, the shrubland in the Altiplano zone showed lower levels of susceptibility, followed by the forests of the Centro and Media zones with medium-high susceptibility to deforestation. Both approaches also agreed that more than 70% (71% General model and 79.7% adding all zones individually) of remaining rainforests (361 880 ha) have high-very high susceptibility to deforestation (Fig. 7). These ecosystems are the largest reserves of forest biomass (> 150 $Mg \cdot ha^{-1}$) (Návar 2011), and represent a serious threat to global warming, if they release all the CO_2 contained in their wood to the atmosphere. About 20% (19.7% model General, 21.2% adding all zones individually) of remaining temperate forests (567 243 ha) of the study area are faced with high and very high susceptibility to deforestation. While about 4% (3.8% model general, 5.2% adding all zones individually) of the remaining shrubland (2 938 332 ha) has high and very high susceptibility. These results reveal the threat to the tropical ecosystems remaining in the study area. Flamenco-Sandoval et al. (2007) found higher rates of deforestation for the rainforest (3.2% per year) than for temperate forests (1.0%) in a forested area of southern Mexico.

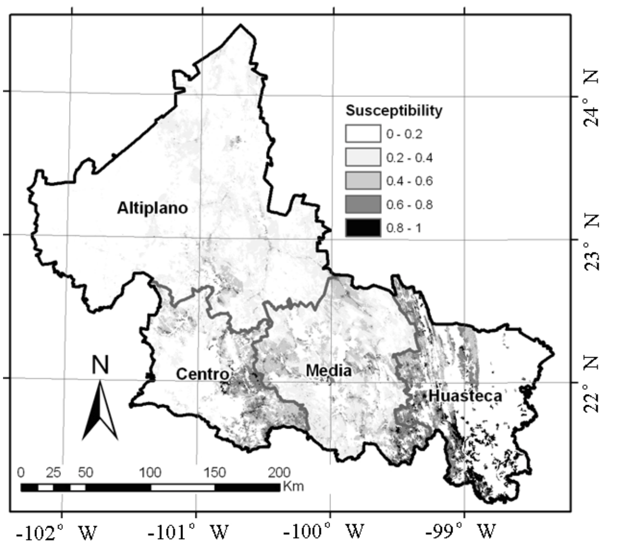

Fig. 5 Estimation of susceptibility to deforestation in San Luis Potosi, Mexico: Model General.

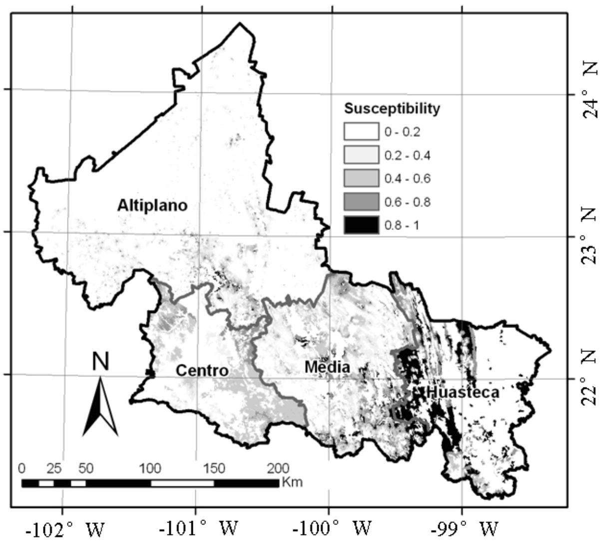

Fig. 6 Estimation of susceptibility to deforestation in San Luis Potosi, Mexico: adding all zones individually

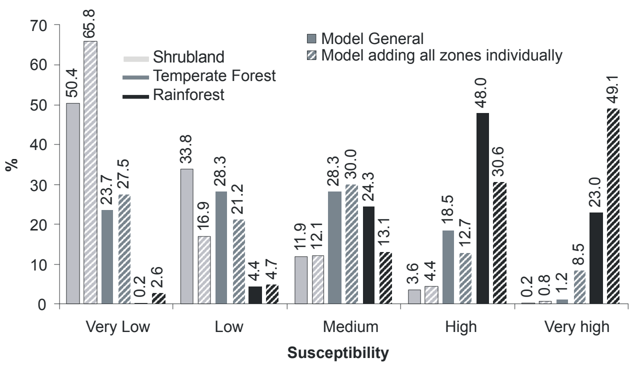

Fig. 7 Percentage of remaining vegetation area by susceptibility levels to deforestation in San Luis Potosi, Mexico: shrubland (2 938 332 ha), temperate forest (567 243 ha), and rainforest (361 880 ha).

The study of deforestation under different focuses, in this case, general and biogeographical zone helps to understand the duality of relationships that can exist as underlying factors of deforestation. Bhattarai et al. (2009) studied deforestation in Nepal considering physiographic provinces based on the elevation above sea level. They also found dual relationships in elevation, distance to roads, and agricultural land. An example in our study is the population density and the number of housing loans: the Altiplano model showed a positive correlation, while in the Huasteca the correlation was negative, and both relationships are true. In the first case, municipalities with higher population density and more housing loans exert more pressure on forest resources by encouraging deforestation, while in the second case the woods and forests are more exposed in those municipalities with less population and fewer housing loans, but the people depend more directly on forest resources, such as firewood. Thus, population density may not always be directly correlated with deforestation. Another example of duality is the variable distance from grasslands. In the General, Centro and Huasteca models, deforestation occurred in areas removed from grasslands, while the opposite happened in the Media and Altiplano models.

Alix-Garcia (2007) found that both slope and elevation had an inverse relationship to land use change. The same relationship was found in our study. Freitas et al. (2010) found a direct relationship between deforestation and the density of roads in southeastern Brazil, implicating the human factor as an agent of change. In our study, also, the areas closer to roads and towns were more prone to deforestation.

The fact that a variable is significant does not necessarily indicate causality. More timber production and greater deforestation (General model and Huasteca) are probably not due to forest management, but simply because there is vegetation that can be removed (shrubland, temperate forest or rainforest). The forest lands that are not essentially subject to regulation or control typical of a forest management program are at greater risk of forest degradation, followed by deforestation. Pineda-Jaimes et al. (2008) found that deforestation is less likely in forest lands under forest management in Central Mexico.

The percentage of households using firewood for cooking was also significant although the importance value was relatively low. Using wood-saving stoves could be an alternative for families living in forest areas to reduce pressure on forest (Bailis et al. 2007) and at the same time reduce the risk of lung cancer in women (Romieu et al. 2009).

Some researchers underline the effects of protecting forests in conservation efforts. Fuller et al. (2010) found that the risk of deforestation does not vary significantly within or outside protected areas in East Kalimantan, Indonesia. While Flamenco-Sandoval et al. (2007) concluded that although protected forest barriers effectively conserve vegetation, there is strong pressure over forests remaining within the reserve. Pineda-Jaimes et al. (2008) evaluated, among other variables, the percentage of pixels of the municipality within protected areas as an explanatory variable of the percentage of deforestation in hardwood forests. They found positive and negative correlations in the same study.

For the social and political conditions in Mexico, where 70% of forest lands are owned by the people of the social organizations called *ejidos* and *comunidades*, it is best to promote the multiple use of forest resources and foster protection by the owners or holders. Today, governments are transferring ownership and use of forest resources to rural communities as they begin to recognize their inability to ensure the conservation and sustainable use of these resources, and the communities demand their ancestral rights over these territories and the opportunity to benefit directly from their natural resources as a livelihood. In Mexico, there are several experiences of successful forest management that can be complemented by initiatives to reduce emissions from deforestation and degradation (REDD) (Cronkleton et al. 2011) and support the idea of sustainable forest management.

The results presented in this research report contribute to the knowledge of the variables involved in the process of deforesta-

tion in arid, temperate and tropical ecosystems in the state of San Luis Potosi, Mexico, as well as the places most vulnerable to this deterioration. Dividing the study area into biogeographical zones allowed detection of statistically significant relations for each particular area hidden in the General model. Given the ecological variation and the different socioeconomic conditions found in each biogeographical zone, the causes of deforestation in arid, temperate forest and rainforest also differed.

The susceptibility maps obtained do not ensure that the identified areas will suffer deforestation; they only represent a measure of vulnerability based on relationships documented by the cases observed in the cartographic comparison. They also represent an interesting tool for regional planning of the state of San Luis Potosí, Mexico. About 70%, 20% and 4% of the remaining rainforest, temperate forest and shrubland, respectively, are highly and very highly susceptible to deforestation, based on physical, social and proximity underlying factors.

A widely sounded solution for conservation of forest resources is the creation of federal reserves. There is often, however, no consensus among the population and in some cases the result is negative, consequently resulting in the Tragedy of the Commons described by Garret Hardin. To promote the sustainable use of forest resources, it is proposed that technical service providers promote the multiple use of forest resources, e.g. hydrological environmental service projects to benefit owners and holders to encourage aquifer recharge and prevent soil erosion, carbon storage and sequestration projects to mitigate the greenhouse effect, and ecotourism projects to boost the scenic beauty to attract potential ecotourists. Deforested areas represent opportunities for forest plantation projects with species of commercial interest. On the other hand, since the consumption of firewood was significant in both Altiplano and Huasteca zones, a complementary option is to continue promoting the use of wood-saving stoves.

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